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A new integrated approach for ranking and clustering of credit customer (Case study: A large bank in Iran)

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Abstract

This study presents an integrated intelligent algorithm for ranking credit customer in different industry sections. The algorithm has two basic modules that is A2 method which suggested by Hosseininasab et al in 2012 and data envelopment analysis (DEA) with three phases: design, execution and performance assessment. In the design phase, a hierarchical structure of the problem based on A2-DEA method (artificial neural network (ANN), Analytical Hierarchy Process (AHP) and DEA) is built and different criteria's are determined based on reviewing of literature. In the execution phase, the proposed method is tested by real data of large bank in Iran. Finally, performance assessment of proposed method is done in third phases. To show the applicability and superiority of the proposed algorithm, two hundred customers of a large bank in different industry sections are studied. This is the first study that uses present an integrated intelligent algorithm for ranking credit customers. This proposed method is compared with A2 method separately. The implementation results show that this method is significantly valid for ranking credit customers.Comparison of methods shows that although AHP and DEA have benefits, they also suffer from limitations, which can be avoided by the A2-DEA model, also improves the time and cost needed for implementing in comparison.

Keywords: Analytical hierarchy process; artificial neural network; data envelopment analysis; banking

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1. Introduction

As the financial market competes sharply nowadays, the traditional banking profit is largely reduced. This causes banks to focus on consumer banking in order to make higher interest profits, i.e. consumer loans. However, the quality of issuing consumer loans is bank dependent and the audit process is forced to be as simple as possible. Consequently, the potential risk gradually arises. With the rapid growth in credit industry and the management of large loan portfolios, credit rating (or credit scoring) models have been extensively used for the credit admission evaluation.

Credit ratings are an index of credit worthiness. The credit-rating process distinguishes between 'good' and 'bad' credit, including all intermediate shades of gray (Ong,2002). Credit ratings are primarily used to assess credit worthiness, investment risk, and default probability of issuers and issues, including bonds, corporations, and banks. The main differences between long-term and short-term ratings are the period and rating range. The long-term ratings are divided into several categories, ranging from AAA to D, reflecting the highest and lowest credit ratings, respectively. Short-term ratings from AA to CCC can be modified by adding a plus or minussign, indicating relative standing within major rating categories.

A high initial rating indicates a low default probability and high credit worthiness, and vice versa. As mentioned, credit ratings are assigned by agencies, such as Fitch, that are typically considered objective third parties. Thus, credit ratings offer the following benefits (Kumar, & Haynes, 2003): (1) credit ratings can improve firm brand image; (2) credit ratings help investors evaluate and assess the credit risk of specific firms; (3) credit ratings increase financing flexibility for specific firms; and (4) credit ratings highlight key investment targets for investor decision-making and reduce the costs for interested parties associated with collecting information. Given the importance of credit ratings, particularly in investment markets, researchers have attempted to construct automatic classification systems that solve credit-rating problems using statistical and artificial intelligence (AI) techniques(Danenas, Garsva, & Gudas,2011; Huang, 2011; Kuhn, Courtney, Morris, & Tatara, 2010; Yu, Wang, & Lai,2001). Shin and Han(2001) developed a case-based reasoning approach using Korean bond-rating data and 12 variables to forecast firm bond ratings on five scales (i.e., A1, A2, A3, B, and C). Their system had better accuracy at 70.0% than multiple discriminant analysis (MDA) at 60%. Kumar and John (2003), who applied an artificial neural network (ANN) with discriminant analysis (DA) using 14 variables, demonstrated that the ANN performed better than DA. Huang et al.(2004) applied a support vector machine (SVM) and backpropagation neural network (BNN) as a benchmark and used 21 variables from the

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United States and Taiwanese financial markets. The Taiwan data contained 74 cases and the US data contained 265 cases. The SVM and BNN methods achieved an accuracy of approximately 80%. Chen and Shih(2006), who also used an SVM method with 72 input variables to generate credit ratings for the Taiwanese banking industry, achieved an accuracy of 84.62% for four scales – twAA and above, twA, twBBB, and twBB and below (tw denotes Taiwan). Moreover, Pasiouras et al.,(2007) applied a novel multi-group hierarchical discrimination (MHDIS) method to Asian commercial banks using five scales based on Fitch Ratings. Their approach achieved an accuracy of 66.03%, exceeding that of DA at 53.73% and logistic regression (LR) at 47.55%. Florez-Lopez(2007) compared MDA with multinomial logit (ML), ordered logit (OL), decision tree C4.5, Classification and Regression Trees (CART) Gini-univariate, and CART Gini-oblique using a sample of 257 European insurance companies. This analysis revealed that the CART Gini-oblique method performed best, with an accuracy of 74% for the five scales of AA, A, BBB, BB, and B.

It is very important for financial institutions to develop credit rating systems to help them to decide whether to grant credit to consumers before issuing loans. In literature, statistical and machine learning techniques for credit rating have been extensively studied(Chih et al, 2010). Recent studies focusing on hybrid models by combining different techniques have shown promising results. However, there are various types of combination methods to develop hybrid models. It is the first study that new method(A2) is integrated by DEA. A real world dataset from a bank in Iran is considered for the experiment. The experimental results show that the proposed integrated hybrid model can provide the highest prediction accuracy and maximize the profit.

The credit rating models are developed to classify loan customers as either a good credit group (accepted) or a bad credit group (rejected) with their related characteristics such as age, income and marital status or based on the data of the previous accepted and rejected applicants(Chen and Huang,2003). The benefits of considering credit scoring include reducing the cost of credit analysis, enabling faster decisions, insuring credit collections, and diminishing possible risks(West,2000). Even if a slight improvement in credit scoring accuracy might reduce, large credit risks and translates into significant future savings.

The traditional approach to predict the consumers' credit risk is based on some statistical methods, such as logistic regression. However, related studies have shown that machine learning techniques or data mining techniques, such as neural networks, decision trees, etc., are superior to traditional (statistical) methods(Crook et al,2007; Huang et al, 2004; Ong et

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al, 2005). That is, using machine-learning techniques can provide higher predication accuracy (Tsai Et al., 2010).
This article presents the development of a conceptual framework, which aims to ranking the different industry sections for issuing loan based on multiple factors. The proposed conceptual framework combines the A^2 method which suggested by Hosseininasab et alin 2012 with the non-parametric technique known as DEA with three phases: design, execution and, validation and verification. This approach uses the result of AHP and DEA as input values of the Artificial Neural Network (ANN) model for developing and improving the model, which Hosseininasab et al. proposed in 2012, with a little change based on the experience of experts in the field. We have named this method A^2-DEA. For comparing this new method, we have used the A^2 methodology to determine the priority of different industries for issuing loan. In other words, in this paper we have proposed a new method named A^2-DEA and have compared it with the A^2 method. In spite of A^2 having advantages, there are also some limitations which include the lack of ability in having objective decision while it is based on subjective decision. We have omitted these limitations by proposing the A^2-DEA method. Increased speed of implementation, decreased cost, ability of both subjective and objective decision, ability of analyzing several scenarios in short time and low cost, are some of the A^2-DEA advantages. In this study, we have followed these questions: 1- How can we assess the ranking of industries for issuing a financial institution special bank by the A^2-DEA and A^2 methods? 2- What are the advantages of the A^2-DEA method to the A^2 method? How can we analysis several scenarios by the A^2-DEA method?
The remainder of this paper is organized as follows; Section 1.1 is devoted to introducing the AHP approach introduced by Herrera-Viedma (2004). In sections 1.2 and 1.3 briefly presents the well-known Artificial neural network (ANN) and data envelopment analysis (DEA). The details of the research methodology are illustrated in section 2. Then in section 3, the experiment and the actual case study of this study is presented. Section 4 discusses the results and scenarios, and Section 5 presents the concluding remarks of this study.

1-1. Analytical hierarchy process (AHP)

The AHP is based on pairwise comparison judgments and can provide a flexible and powerful tool for handling both qualitative and quantitative multi-criteria problems, which is developed by Saaty (1980). Its main distinction is that AHP has been applied to a wide variety of decisions (Ngai, &Chan, 2005; Mohajeri & Amin, 2010). AHP provides an estimate of additive utility weight that best matches the initial information provided by

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the decision-maker and it provides a meaningful way to measure and combine tangible and intangible criteria in any decision (Kokangul, &Susuz, 2009 ; Lozano , Villa, & Canca, 2011). It can also be used with other techniques. For instance Wanichpongpan et al. (2007), Hermann et al. (2007) and Kim et al. (2009) used AHP and Life Cycle Assessment (LCA) as decision support tool or multi-criteria analysis tool in fields of assessing environmental performance or assessing the recycling potential of materials. In this paper we integrate AHP and ANN to consider not only qualitative and quantitative factors but also having a lot of scenarios in short time and low cost. The traditional AHP uses n×(n-1)/2 judgments in a preference matrix with n alternatives. Because of that, it takes a long time to collect judgments and to do calculations. In this study, rather than using conventional AHP, the pairwise comparison approach is based on the model, which Herrera-Viedma proposed in 2004. This method considers only n-1 judgments and enables decision makers to express their preferences over a set of alternatives with the fewest judgments; it also avoids checking the consistency in the decision-making process (Wang and Chang, 2007). In section 4, this method is explained by means of an empirical case.

1-2.Artificial neural network (ANN)

A neural network is a simplified model of the way the human brain processes information. ANNs mimic the ability of the biological neural systems in a computerized way by resorting to the learning mechanism as the basis of human behavior (Cui, & Han, 2008). ANNs are a class of flexible non-linear models that can find patterns adaptively from the data. Theoretically, it has been demonstrated that given an appropriate number of non-linear processing units, ANNs can learn from experience and estimate any complex functional relationship with high accuracy. Their approximating power comes from the parallel processing of the information from the given data. ANNs have been broadly applied to many estimating problems. For instance Kuo et al. have integrated ANN and two multi-attribute decision analysis methods to develop a green supplier selection model (Kuo et al., 2010). The main reason for their success is that they are capable of discovering the hidden relationship (mapping) in data. ANNs have a lot of application in recent years. In 2012 Liao presented a general methodology for developing environmental emergency decision support systems (EEDSS) based on ANN (Liao et al, 2012).
The ANN `learns' the governing relationships in the input and output data sets by modifying the weights between its nodes. In essence, a trained ANN model can be viewed as a function that maps input vectors to output vectors. Single hidden layer network based on Back Propagation (BP) learning is the

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most widely used model form for estimating (Zhang and Qi, 2005). BP learning is a kind of supervised learning introduced by Werbos (1974) and later developed by Rumelhart & McClelland (1986).

At the beginning of the learning stage all weights in the network are initialized to small random values. The algorithm uses a learning set, which consists of input – desired output pattern pairs. Each input – output pair is obtained by the offline processing of historical data. These pairs are used to adjust the weights in the network to minimize the Sum Squared Error (SSE). This error function measures the difference between the real and the desired values over all output neurons and all learning patterns. After computing SSE, the back propagation step computes the corrections to be applied to the weights.

The architecture of ANN model usually consists of threeparts: an input layer, the hidden layers and an output layer. The information contained in the input layer is mappedto the output layer through the hidden layers. Each neuroncan receive its input only from the lower layer and sends itsoutput to the neurons only on the higher layer.

To find out the most reliable model, several performance indicators can be used. The performance of the ANN models based on their reliability is evaluated by a regression analysis between the predicted values by the ANN models and the actual values. The indicators used with aim of performance evaluation for both training and test data sets are the root mean square error (RMSE) and correlation coefficient (Hosoz, and Ertunc, 2007). The root mean square error is calculated by:

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2} \quad (1)$$

Where $\hat{y}_i$ is the predicted value by the ANN model, y_i is actual value and m is the number of points in the data set. The absolute fraction of variance, a statistical criterion that can be applied to multiple regression analysis, is calculated by:

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{m}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{m}(y_i - \bar{y})^2}\right) \quad (2)$$

The absolute fraction of variance ranges between zero and one. Ideally, R^2 should be close to one, whereas a poor fit results in a value near zero.

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1-3. Data envelopment analysis(DEA)

DEA is a methodology based on applications of linear programming. It has been successfully employed for assessing the relative performance of a set of firms, usually called decision making units (DMU), which uses a variety of identical inputs to produce a variety of identical outputs. The basic ideas behind DEA date back to farrel , but the recent series of discussions started with the article by chames et al(1985). We give very briefly the salient features of DEA, more detailed information can be obtained elsewere in(Jamas and Pollitt,2003; Jamas et al., 2004; Giannakis et al., 2005).

Assume that there are n DMUs which convert I input to J outputs. In particular, the mth DMU produces outputs y_{jm} using x_{im}inputs. To measure the efficiency of this conversion process by a DMU, a fractional mathematical programming model, denoted by model (1) is proposed. The objective function of the model maximizes the ratio of weighted outputs to weighted inputs for the DMU under consideration subject to the condition that the similar ratios for all DMUs are less than or equal to 1. Hence, we have

Model (1) : Max $\frac{\sum_{j=1}^{J} y_{jm} v_{jm}}{\sum_{i=1}^{I} u_{im} x_{im}}$

S.t $0 \leq \frac{v_{jm} y_{jn}}{u_{im} x_{in}} \leq 1$, n=1, 2,…, N (3)

$v_{jm}, u_{im} \geq \varepsilon$, i=1, 2,…, I; j=1,2,…, J

Where subscripts i, j and n stand for inputs, outputs, and DMUs, respectively. The variables $y_{jm}$and $u_{im}$are the weights to be determined by the above mathematical program. The term e is an arbitrarily small positive number introduced to ensure that all of the known inputs and outputs have positive weight values. The mth DMU is the base DMU in the above model. The optimal value of the objective function of model (1) is the DEA efficiency score assigned to the mth DMU. If the efficiency score is 1 (or 100%), the mth DMU satisfies the necessary condition as DEA efficient. Otherwise, it is considered as DEA inefficient. Note that the inefficiency is relative to the performance of other DMUs under consideration.

It is difficult to solve the above model because of its fractional objective function. However, if either the denominator or numerator of the ratio is forced to be unity, then the objective function will become linear, and a linear programming problem can be obtained. By setting the denominator of the ratio equal to unity, we can obtain the following output maximization

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linear programming problem, denoted as model . Therefore, it is possible to produce the input minimization linear programming problem.

Model (2): Max $\sum_{j=1}^{J} v_{jm} y_{jm}$

S.t $\sum_{i=1}^{I} u_{im} x_{im}$=1 (4)

$\sum_{j=1}^{J} v_{jm} y_{jn}$- $\sum_{i=1}^{I} u_{im} x_{in} \leq 0$, n=1, 2,…, N

$v_{jm}, u_{im} \geq \varepsilon$, i=1, 2,…, I; j=1,2,…, J

A complete DEA exercise involves solution of N such models, each for a base DMU (m = 1, 2,.., N), yielding N different set of weights (v_{jm}, u_{im}). In each model, the constraints are the same while the ratio to be maximized is changed. DEA literature uses more advanced concepts such as the dual of the previous model (model (2)), and incorporation of returns to scale. There are also many extensions to the basic models described here (Jamas et al., 2004). Charnes et al have provided detailed accounts of the important developments in the history of DEA(Giannakis et al., 2005). Thus, DEA has the ability to give a single index of performance, usually called the efficiency score, synthesizing diverse characteristics of different DMUs. Because of this ability, DEA has received numerous applications over the past two decades.

2. Methodological approach

Saaty (1980) developed the AHP method to solve the problems of multi criteria decision-making (MCDM) for determining the rank or preferences of decision alternatives. To use the AHP model, groups of expert opinion of decision makers are needed, which it is time consuming and costly. Therefore, we cannot use AHP easily for introducing several scenarios. To remove these shortcomings, Hosseininasab et al. had proposed the integration of the AHP and ANN models, which called A^2 in 2012. Because this method has many benefits we integrate this method as subjective tool with DEA as objective tool. One of the important benefits of using ANN is the ability of generalizing variables, which are gained from a real world problem. It is also useful for presenting several scenarios as an accurate, fast running, and inexpensive method for decision makers (Yazgan, 2009). In the proposed model, when AHP-DEA and ANN models are set up, measuring the priority of industries for issuing loan when the budget is limited, can be made easy by the opinions of a few decision makers, thus the calculation of the geometric mean of answers that are obtained from many experts will be

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unnecessary. Additionally, with ANN, we can analyze many scenarios with the change of any criteria of AHP-DEA in a short time. In the next step, we have compared the proposed model with the A^2 model. We have used this model for comparing, because the aim of the A^2 model is to avoid reassessment while decreasing cost and having subjective tool. In the proposed model, the major criteria of the assessment process were identified with the help of review of literature, and experience of experts in the field. In this model, an AHP-DEA structure was proposed in which the criteria's weights were determined for every decision maker. An ANN model was implemented and trained by using AHP-DEA results in order to avoid using the AHP-DEA model. It causes decreased execution time and increased efficiency of result. The details of ANN procedure have been shown in Fig. 1-a, and are explained briefly in section 2.2. The priority of industries, which is determined in ten sections (I1-I10) by experts, is achieved from running the ANN model. Although using ANN helps avoid aggregation of decision makers' judgments by an average method, the most important contribution of this study is that it provides decision makers with useful scenarios about influential criteria to make decisions concerning which industries would be better to be selected to issue loan in tow subjective and objective perspectives. For comparing and surveying benefits and limitations of the proposed model, we apply the A^2 model, which is explained briefly in section 2.2 (see Fig. 1-b).

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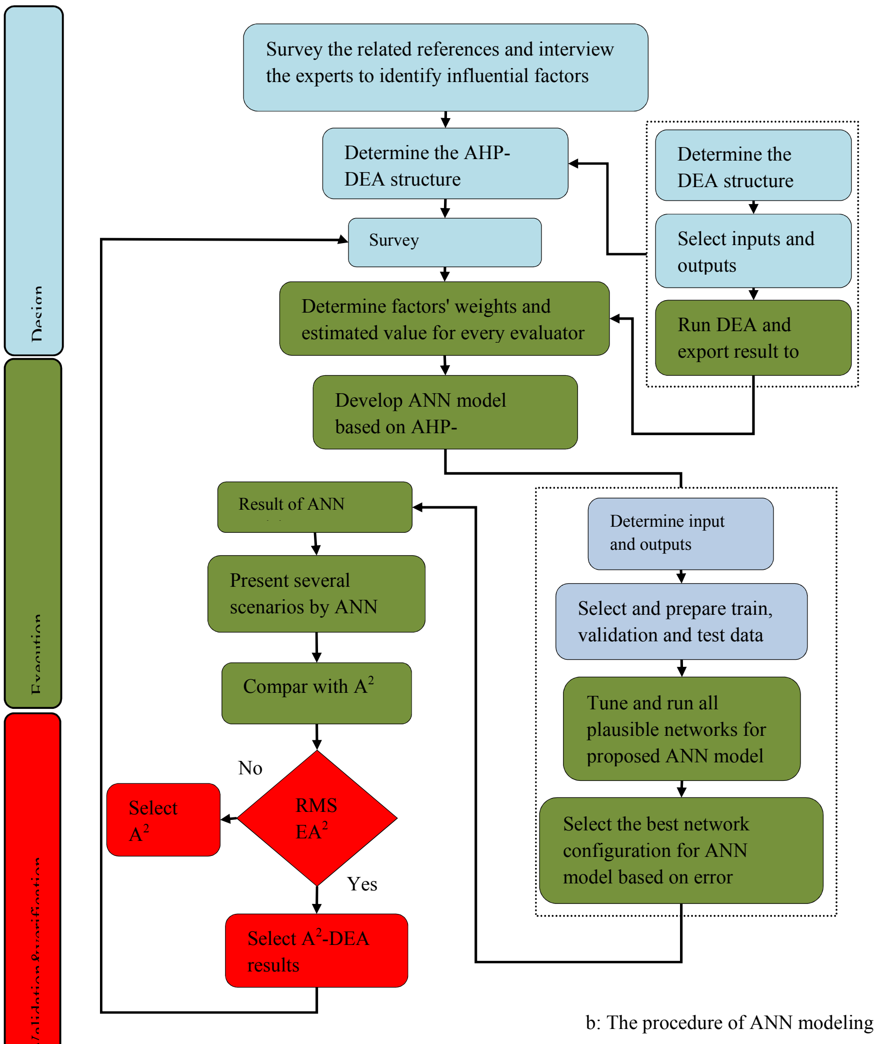

b: The procedure of ANN modeling

a:The main proposed procedure

Fig. 1 The procedure of measuring the priority of industries for issuing loan in two subjective and objective perspectives (A^2-DEA)

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2-1. The selection criteria and building of the AHP-DEA model

The first step in developing the AHP-DEA model is building a hierarchical structure of the problem. The goal and all the decision criteria are classified into three major levels. In the first step of the application of the AHP-DEA model, the decision hierarchy of the AHP model is constructed to rank credit customers in different industries. The goal of the AHP-DEA model is placed at the first level of the hierarchy. For selecting the factor of second level, we surveyed the literature (see

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Table۱). In order to obtain further information to identify and categorize the criteria affecting the clients credit rating applying for banking facilities, as the most important step, these criteria have been identified and categorized through the literature review. Then, these criteria and the related clusters have been improved through several interviews with senior experts from different bank branches and banking facility applicants. The summary of the final criteria and their clustering is provided in

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Table١.

In order to determine the validity level of the criteria, the opinions of the banking credit experts, financial managers, financial experts and credit applicant experts have been taken into account. Stability of these criteria has been calculated through the Cronbach's Alpha method and has been verified by 86%.

Static population in this study has been drawn based on the investigation and consultation with filed senior experts and as a result, 35 companies that have received the large bank financial facilities from 2009 to 2010 and were listed in the Tehran Stock Exchange have been selected. These information and financial ratios have been completed with respect to the Stock Exchange rules and regulations and are homogenous and highly accurate. Also, access to the financial information of the selected companies is easier in this way.

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Table۱- Comparative Studies for selecting factors of second level of AHP-DEA

DEA Info		AHP_DEA Info	Factors	Authors
Variable	IN/OUT	labels'		
Input	In(1)	E1	Capital	Cummins et al(2002) , Feroz et al 2(2003)
	In(2)	E2	Retained Profit	Aitman (1998), Feroz et al 2(2003), Cheng et al(2007)
	In(3)	E3	Current Liability	Liang et al(2006)
	In(4)	E4	Long-term Liabilities	Omero et al(2005), Molhotra et al(2008)
	In(5)	E5	Legal reserves	-
Output	Out(1)	E6	Interest Coverage Rate	Liang et al(2006), Cheng et al(2007), Molhotra et al(2008), Margaritis et al(2009)
	Out(2)	E7	Asset Return Ratio	Brid(2001), capobianco et al(2004), Duzakin et al(2007), Molhotra et al(2008)
	Out(3)	E8	Quick Ratio	Duzakin et al(2007)
	Out(4)	E9	Average Collection Period	Feroz(2003)
	Out(5)	E10	Return on Shareholder's equity	Margaritis et al(2009), Brid(2001), Liang et al(2006)

These ten factors plus last factor, which is related to result of DEA, are placed at the second level of the hierarchy. In other words, according to Fig 2, the eleventh factor is related to DEA's results. In fact, the efficiency scores measured by DEA are placed in AHP. Determining of inputs and outputs is one of the most important steps of DEA method.

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Table١ shows the structure of DEA based on literature review.
For determining the third level of AHP structure, we used the company's cllasification. Debt collection constitutes a considerable amount of financial resources required for banking operations. For banks that have been unsuccessful at collecting debts, it means the loss of a considerable part of assets and financial resources for banks. Therefore, banks try to properly evaluate the credit applicants more efficiently using different methods in order to reduce the credit and facilities non-pay off risk. The companies for the statistical sample have been chosen from 10 different industries including: food, pharmaceutical, electrical devices, automotive, basic metals, cement and plaster, manufacturing equipment and machinery, telecommunications, glass and crystal and mineral industry. The most notable companies among these industries include Iran Khodro, Saipa, Shahab Khodro, Loghman Pharmaceutics, Azadeghan Cement, Khoozestan Steel, Esfahan's Mobarakeh Steel and Machine Sazi Arak Co.

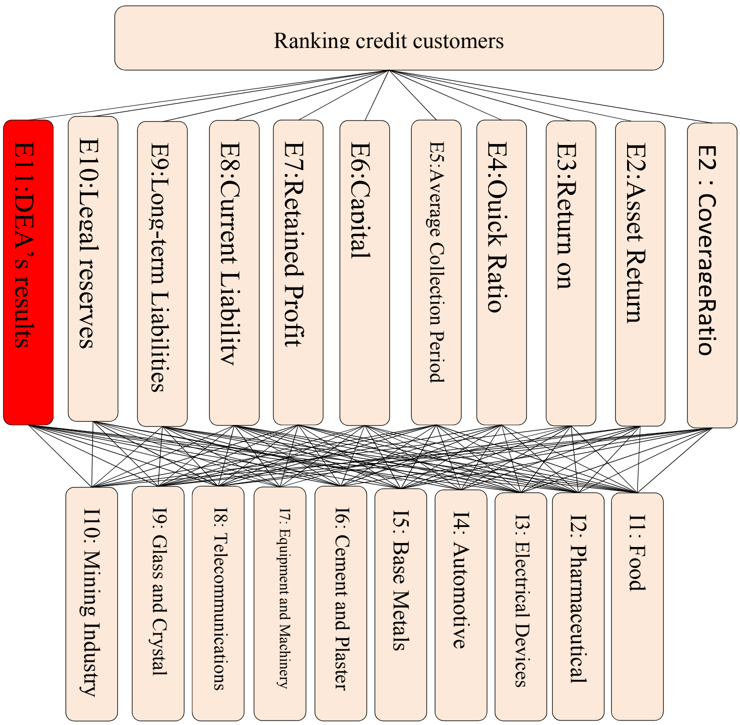

Fig. **2** describes the hierarchy of the AHP-DEA model.

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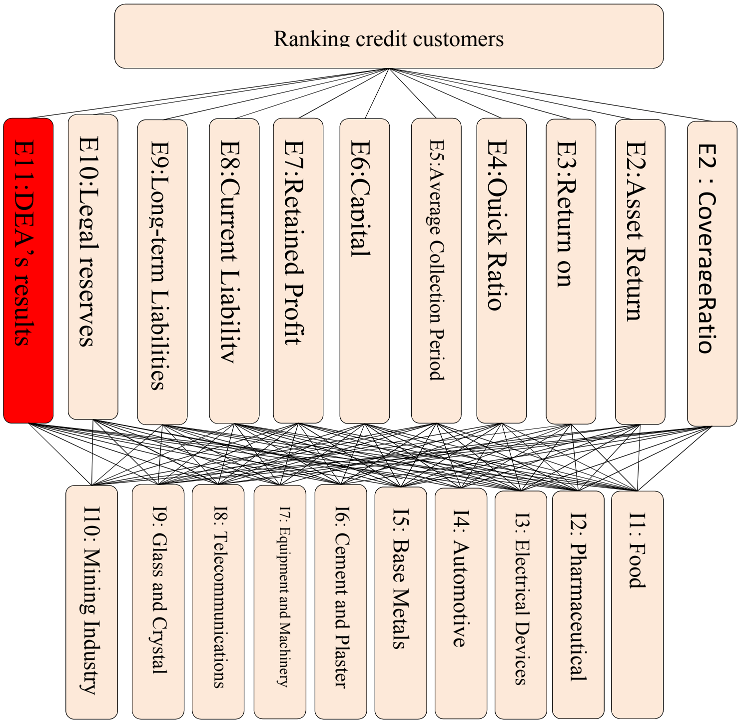

Fig. 2.The hierarchy framework for ranking credit customers

2-2. The building of the A^2-DEA model

The steps of ANN modeling are according to the integrated AHP-ANN(A^2)–DEA approach. The proposed hybrid A^2–DEA model has the following basic steps:

Step 1: Determine the input and outputs variables: This decision addresses the definition of the input variables (e.g., rate of any criteria) and the output variables (e.g., section of industries) in order to assign them to the network of each model as inputs and outputs, respectively. In addition, the way of presenting data to the network have to be determined. One way to dothis is to present all available process variables asnetwork inputs, and then let the network modifyitself during training so that the connection of any insignificant variables becomes weak. Another approach is to be more selective, and introduce as inputs only those variables that are surely affecting on the process of outputs. The first approach is called the ‘‘global

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network'' while the second is termed the ''focused network'' (Wilcox and Wright, 1998).

Step 2: Select and prepare the train, validation and test data set: In the data selection step, it is necessary to ensure the sufficiency and integrity of the data used to train and test the network, whereas the network performance can be directly influenced by the presented data. It is not simply possible to say how many data sets are required, because this depends on the nature of the process modeling problem and the cost of providing data.

The prepared data set is categorized randomly into three sets: Train, validation, and test data sets. Generally, the training data should cover the whole of data variation range. The validation data set is used to ensure that there is no over-fitting in the final result. In order to validate the models, a data set is selected randomly from training data. When a significant over-fitting has occurred, the error of validation data starts to increase and the training process is stopped.

In order to enhance the model fitness, several tasks for preparing data may be performed such as: (1) data integrity check, (2) extreme data removal, (3) data scaling, and (4) data coding. Scaling of the data is automatically carried out during the training phase of the ANN. Data are preprocessed (scaled to [0, 1]) through dividing each dataset by its norm. Finally, our outputs are post-processed and returned to their original scale.

Step 3:Tune and run all plausible networks for proposed ANN model: Developing an ANN model includes determining the number of layers, the number of neurons in each layer, each layer's transfer function, and how the layers are connected to each other. The performance of an ANN model depends on the fitness of the network features. For instance, too few neurons may result in under-fitting, but too many neurons may yield over-fitting, which means that all the training data fit well, but ANN model performance for test data is low. The optimal configuration of each model is selected according to the training process results. Therefore, various architectures for each network are proposed with diverse features. During the training process, representative examples of inputs and their corresponding outputs are presented to the models. Each ANN model that its network trained and learned the governing relationships in the data set by modifying its weights and biases, called the fitted model. Ultimately, the optimal configuration for each network based on the user-specified error function is chosen by trial and error.

There are various training algorithms to fit ANN models. The most popular algorithm in optimization and estimation applications is the standard back propagation (BP) (Nascimento, 2000). This algorithm is a widely used

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iterative optimization technique that locates the minimum of a function expressed as equation5.

$$E = \frac{1}{2}\sum_{m}\left(y_{dm} - y_{m}\right)^{2} \qquad (5)$$

Where, y_{dm} is the target value of the output layer, and y_m is the ratiocinated value of the output layer. Based on BP algorithm, during the training process, the deviation between the network output and the desired output at each presentation is computed as an error. This error, in the quadratic form, was then fed back (back propagated) to the network and used for modifying the weights by a gradient descent method.

The training process carries on while one of three user-specified conditions is met at least. Theseconditions consist of (1) exceeding the maximum number of epochs, (2) meeting the performance goal, and (3) decreasing of the gradient descent rate to the less than the allowable limit.

Step 4:Select the best network configuration for ANN model based on error function: The optimal configuration of each model is selected according to the training process results. Therefore, various architectures for each network are proposed with various features. During the training process, representative examples of inputs and their corresponding outputs are presented to the models. Each ANN model that its network trained and learned the governing relationships in the data set by modifying its weights and biases, called the fitted model. Ultimately, the optimal configuration for each network based on the user-specified error function is chosen by trial and error.

3. Model development and experimental details

A real world decision-making problem in ranking of credit customer for a case project (a large bank in Iran) is adopted as a case study. In this problem, both the A^2 approach and the proposed A^2-DEA are applied for ranking of credit customers.

3-1. Experimental details of proposed model (A^2–DEA model)

Step 1: Collecting data and calculating the weights of the criteria

Collecting the expert judgment for running AHP-DEA model is very important and because of the large number of decision makers, it is a challenging work. The model which Herrera-Viedma proposed in 2004 helps the decision maker to express his or her opinion easily in a short time. A special questionnaire for AHP which Wang et al., (2007) has proposed was used to complete a pairwise comparison matrix.

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For applying the A^2-DEA model, a team of decision makers has completed the questionnaire according to current organization strategy. The team consists of 85 experts, including managers and experts from six departments of the bank. For instance, 5 judgments of decision makers for a set of ten adjoining factors {E1.E2, E2.E3, E3.E4, E4.E5, E5.E6, E6.E7, E7.E8, E8.E9, E9.E10 and E10.E11} are listed as follows (
Table **1**):

Table 1.The judgment scores for nine criteria's evaluated by ten decision makers

	DM1	DM2	DM3	DM4	DM5	
E1	4:1	3:1	1:1	6:1	7:1	E2
E2	1:5	1:2	1:1	1:8	1:3	E3
E3	1:7	1:9	1:5	1:6	1:9	E4
E4	2:1	3:1	6:1	1:1	4:1	E5
E5	1:9	1:5	1:6	1:2	1:8	E6
E6	2:1	2:1	4:1	4:1	1:2	E7
E7	1:4	1:4	2:1	1:5	1:8	E8
E8	6:1	8:1	6:1	5:1	5:1	E9
E9	9:1	8:1	4:1	3:1	3:1	E10
E10	1:9	1:3	5:1	4:1	1:2	E11

According to
Table **1**, every DM must fill only 10 cells. The DM must compare 2 factors with each other. In this stage, the DM should ask himself/herself this question and answer it by 9 scales: which factor (for example E1 and E2) is more important in respect to every section of industries and how much does it rate.

The following is the steps for calculating factors' weight based on Herrera-Viedma' model (2004) after collecting the opinions. To illustrate these steps, the assessment of decision maker 1 is selected as an example here.

Table 2 is the pairwise comparison matrix of decision maker 1 which shows theimportance of each two adjoining factor for a set of n - 1 preference values.

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Table 2.First step of pairwise comparison matrix of decision maker 1

	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11
E1	1	4.00	x	x	x	x	x	x	x	x	x
E2	x	1	0.20	x	x	x	x	x	x	x	x
E3	x	x	1	0.14	x	x	x	x	x	x	x
E4	x	x	x	1	2.00	x	x	x	x	x	x
E5	x	x	x	x	1	0.11	x	x	x	x	x
E6	x	x	x	x	x	1	2.00	x	x	x	x
E7	x	x	x	x	x	x	1	0.25	x	x	x
E8	x	x	x	x	x	x	x	1	6.00	x	x
E9	x	x	x	x	x	x	x	x	1	9	x
E10	x	x	x	x	x	x	x	x	x	1	0.11
E11	x	x	x	x	x	x	x	x	x	x	1

In thisstep, the elements are transformed into an interval [0, 1] by equation6 inwhich $a_{ij} \in [۱:۹,۹]$ and $W_{ij} \in [۰,۱]$.

$$W_{ij} = (۱/۲)(۱ + \log_{۹} a_{ij}) \tag{6}$$

where W_{ij} indicates the lack of indifference between factors i and j, $W_{ij} = ۱$ suggests that factor i is absolutely more important than the factor j, $W_{ij} = ۰$ denotes that factor i is absolutely less important than the factor j, and $W_{ij} > \frac{۱}{۲}$ reveals that the factor i is preferred to factor j.

To calculate the remaining elements, equation's7 and 8 are used .

$$W_{ij} + W_{ji} = ۱ \qquad \forall\, i,j \in \{۱,...,۹\} \tag{7}$$

$$W_{ji} = ((j - i + ۱)/۲) - W_{i(i+۱)} - W_{(i+۱)(i+۲)} - W_{(i+۲)(i+۳)} - .... - W_{(j-۱)j} \tag{8}$$

If this preference matrix contains any values that are not included in the interval [0,1], but in an interval [-a,1 + a], then a transformation function is required to preserve the reciprocity and additive transitivity. The transformation function is given by equation 18 where a indicates the absolute value of the minimum in this preference matrix.

$$f(W_{ij}) = w_{ij} = (W_{ij} + a)/(۱ + ۲a) \tag{9}$$

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Final weight is achieved by using the average of the normalized matrix row. The normalized matrix and final priority of influential factors for decision maker 1 are shown in Table 3 .

Table 3.Normalized weight matrix and priority of influential factors

	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	Priority	Rank
E1	0.070	0.073	0.069	0.061	0.065	0.050	0.056	0.040	0.059	0.069	0.059	0.061	10
E2	0.053	0.059	0.052	0.038	0.044	0.017	0.028	0.000	0.033	0.051	0.033	0.037	11
E3	0.073	0.075	0.072	0.065	0.068	0.055	0.060	0.047	0.063	0.072	0.063	0.065	9
E4	0.096	0.095	0.096	0.098	0.098	0.101	0.100	0.104	0.099	0.097	0.099	0.099	6
E5	0.088	0.088	0.088	0.087	0.087	0.085	0.086	0.084	0.086	0.088	0.086	0.087	7
E6	0.115	0.111	0.115	0.124	0.120	0.137	0.130	0.148	0.127	0.116	0.127	0.125	2
E7	0.106	0.104	0.107	0.112	0.110	0.121	0.116	0.127	0.114	0.107	0.114	0.113	3
E8	0.123	0.118	0.124	0.136	0.131	0.154	0.144	0.168	0.140	0.125	0.140	0.137	1
E9	0.101	0.100	0.101	0.105	0.104	0.111	0.108	0.116	0.107	0.102	0.107	0.106	4
E10	0.074	0.077	0.074	0.068	0.070	0.059	0.064	0.051	0.066	0.074	0.066	0.068	8

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E11	0.101	0.100	0.101	0.105	0.104	0.111	0.108	0.116	0.107	0.102	0.107	0.106	5

The above stage is applied for calculating other decision makers' matrix too.

Step 2: Calculating the weight of section of industries.

Using ten options as AHP outcome (I1 to I10) causes, the calculation of final priority gets easy.Table **4** is the list of five numbers of the pairwise comparison matrices for a set of ten possible outcomes as an example.

Table 4.The judgment scores given to the priority of section of industries

factors	Industry sections	DM1	DM2	DM3	DM4	DM5	Industry sections
	I1	1:3	1:2	3:1	2:1	1:2	I2
E1	I2	4:1	1:1	2:1	3:1	2:1	I3
	I3	1:1	1:2	1:3	2:1	1:3	I4
	I4	1:4	1:2	1:4	1:5	1:2	I5
	I5	1:1	2:1	2:1	2:1	1:2	I6
	I6	2:1	4:1	3:1	3:1	2:1	I7
	I7	1:4	1:2	1:4	1:4	1:1	I8
	I8	1:3	2:1	1:2	3:1	3:1	I9
	I9	5:1	5:1	4:1	3:1	4:1	I10
.	.						.
.	.						.
.	.						.
E9							
✷✷E10	I1	1:3	1:1	1:5	1:2	1:4	I2
	I2	2:1	1:1	3:1	2:1	3:1	I3
	I3	1:2	1:4	1:1	1:2	2:1	I4
	I4	1:4	1:3	1:2	1:4	1:3	I5
	I5	2:1	3:1	5:1	4:1	4:1	I6
	I6	3:1	3:1	3:1	2:1	4:1	I7
	I7	3:1	3:1	4:1	4:1	2:1	I8
	I8	2:1	1:1	1:2	2:1	4:1	I9
	I9	4:1	5:1	3:1	4:1	4:1	I10

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✷✷ E1-E10 is related to factors of second level and E11 is related to result of DEA and it is not necessary the judgment scores her.

All the stages described in the previous section, are applied for calculating the priority of outcomes for any decision maker(note that to transform the values and the scale [1: 5,5] into [0,1], the function $p_{ij} = (۱/۲)(۱ + \log_{۵} a_{ij})$ is used instead of equation6.

According to Fig 2, the eleventh of factors is named DEA's results. In step 2 for calculating the weight of section of industries we need the result of running DEA which calculated by the GAMS software and shows in Table 3.

At the end of this section, to obtain the priority of any section of industries we use equation10 and the result is shown in Table 5:

$$ES = \sum_{i=۱}^{۹} p_i w_i \tag{10}$$

Where w_i denotes the estimated weight of i criteria. i, and p_i represents the weight of the possible outcome, concerning influential criteria i.

Table 5. Priority of every section of industries by decision maker 5

	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	✷E11	Priority	Rank
	0.061	0.037	0.065	0.099	0.087	0.125	0.113	0.137	0.106	0.068	0.106		
I1	0.059	0.060	0.141	0.133	0.101	0.095	0.069	0.069	0.093	0.081	0.073	0.089	10
I2	0.03	0.101	0.109	0.117	0.079	0.081	0.171	0.142	0.102	0.110	0.058	0.104	3
I3	0.062	0.081	0.171	0.064	0.158	0.123	0.035	0.139	0.060	0.077	0.092	0.098	5
I4	0.16	0.161	0.137	0.118	0.079	0.155	0.069	0.110	0.118	0.145	0.115	0.120	1
I5	0.092	0.181	0.084	0.070	0.118	0.045	0.103	0.069	0.088	0.110	0.149	0.094	8

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I6	0.166	0.151	0.107	0.094	0.060	0.115	0.137	0.109	0.086	0.080	0.143	0.112	2
I7	0.121	0.085	0.066	0.167	0.080	0.078	0.109	0.076	0.131	0.104	0.092	0.101	4
I8	0.061	0.063	0.082	0.064	0.155	0.077	0.070	0.069	0.123	0.141	0.120	0.094	9
I9	0.149	0.077	0.064	0.061	0.064	0.077	0.119	0.110	0.110	0.112	0.093	0.095	7
I10	0.101	0.040	0.038	0.114	0.105	0.153	0.116	0.109	0.088	0.041	0.066	0.097	6

✷The result obtained by DEA

Now we have 85 comparison matrices with final results. In traditional AHP model, some methods such as the average value are used for the integration of the judgment values of the decision makers. In this study, to avoid using averages and to have a capability of different scenarios about influential factors, the ANN model was used as follows.

Step 3: Ranking of credit customer by ANN

Adopting a global approach in presenting the data to the network, the ANN model for the measuring the rank of credit customer in different industries sections was trained by BP algorithm based on Levenberg-Marquart rule. This ANN model includes eleven inputs that consist of the weight of "E1" to "E11" obtained from AHP model while it has ten outputs, which are the priority of "I1" to "I10". The obtained data form AHP results are divided into 85% as the train data and the rest (15%) as the test data.
To choose the optimal network of the ANN, a number of different network configurations, including one hidden layer and different numbers of neurons in hidden layers with various transfer functions were provided. However, in this network, selection of more than one layer leads to a decrease in the network training performance. The training process was run in the MATLAB so a minimum of the user-specification error function: i.e., RMSE was reached while the number of epochs is fewer than 3000.
The optimal network for the ANN model was selected based on training and test RMSE of networks. When the number of neurons in the hidden layer

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was equal to 20, it was the least training RMSE of network. The ANN model results are shown in Table 6 .

Table 6. The weight and priority of industries sections that obtain from ANN model

	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10
Weight	0.065	0.0981	0.089	0.153	0.098	0.147	0.099	0.079	0.075	0.089
Priority	10	3	6	1	4	2	5	8	9	7

4. Discussion and scenarios

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Table 7 shows the result of A^2 method and the proposed method. According to this result, there is no significant difference between the results. However, by comparing the process of these two methods, we can sort benefits of A^2– DEA and limitations of A^2 as follows:

The most important ability of proposed method (A^2– DEA) is related to objective and subjective view in decision-making process, while in A^2method only subjective view is noticed.

Another benefit of A^2– DEA is the ability to design several scenarios and analyses in short time. In this section, we show an example of one scenario:

The proposed model was applied to the current situation of the bank and decision makers filled the questionnaires based on the current situation. For designing a scenario, we assume that the current situation can be changed. In this study, when strategy changes, we don't need to have all of evaluator's opinions for solving the model by A^2- DEA. we need to fill only one questionnaire by a decision maker. In this case, one specialist as an evaluator with respect to the assumption will complete the questionnaire. The required input data for ANN could be obtained based on the evaluator opinions. The A^2 – DEA result shows that the new weight of every industry sections in the new assumed scenario is: 0.069, 0.087, 0.071, 0.108, 0.143, 0.162, 0.045, 0.023, 0.163, and 0.128 . Thus, it can be concluded that such a proposed action can cause the increase obtaining of better industry section. Similarly, different scenarios can be presented in order to determine the priority of industry sections according to any strategy status while it is impossible to have several scenarios in short time by other methods.

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Table 7. The result of A^2-DEA and A^2 approaches

Criteria	Average of weightings of criteria			
Weighting approach	A^2-DEA method		A^2 method	
	Level one	Level two	Level one	Level two
E1	0.068		0.089	
E2	0.042		0.085	
E3	0.072		0.075	
E4	0.082		0.121	
E5	0.068		0.086	
E6	0.132		0.15	
E7	0.118		0.039	
E8	0.151		0.059	
E9	0.102		0.181	
E10	0.072		0.115	
E11	0.101		-	
I1		0.065		0.113
I2		0.0981		0.035
I3		0.089		0.095
I4		0.153		0.142
I5		0.098		0.159
I6		0.147		0.137
I7		0.099		0.075
I8		0.079		0.049
I9		0.075		0.096
I10		0.089		0.099

Therefore, by having different scenarios in short time and low cost, the bank can analyze the most appropriate industry section.

5. Conclusion

This paper presented an integrated algorithm based on A^2 and DEA to rank industry section. To show the applicability and superiority of the proposed framework, actual data for the bank in Iran are used. The proposed algorithm may be used to rank industry section in the future by optimizing parameter values. The proposed algorithm first uses AHP structure proposed by Herrera-Viedma and DEA to generate weights of factors for each industry sections. It then run ANN for building expert tools to have ability of analyzing a lot of scenarios in short time and low cost. The outputs of the AHP-DEA are used for ANN model. This paper presented a highly unique flexible A^2-DEA algorithm to rank credit clients in different industry section. Fig.1 represents this algorithm. The A^2-DEA approach considered new indicators in addition to conventional approach. Because of non-linearity of

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the ANN in addition to its universal approximations of functions and its derivate that makes the algorithms highly flexible.

Results showed A^2-DEA provides advantages that are more accurate. The proposed approach is also compared with A^2 in ranking of bank credit customers. Its features are compared with previous models to show its advantages over previous models. The A^2-DEA is capable of dealing both data complexity and ambiguity due to ANN mechanisms.

The proposed model consists of three capabilities. First, by implementing the proposed model we can have different scenarios in a short time and minimum cost for analyzing various strategies in ranking of industry sections. Secondly, in A^2-DEA we have objective and subjective view. In the proposed model, when AHP and ANN models are setup, a priority of sections can be easily made by the opinion of one single expert. In this study, using the AHP model proposed by Herrera-Viedma, it is possible to avoid checking consistency and collecting the experts' opinions in less time, so that the number of pairwise comparison judgments is declined to n-1 whereas the traditional analytic hierarchy approach uses n(n-1)/2 judgments in a preference matrix with n attributes. Therefore, we can see that the proposed model is time consuming.

Most importantly, the integration of AHP, DEA and ANNs improves the ranking of the credit customers in various industry sections. The top management can design scenarios to choose the best decision or actions to select the best company by analyzing different scenarios. Thirdly, by this method management can determine the priority in every short period while the time and cost of estimation is decreased.

6. Limitations and future research

Despite, several benefit of A^2 -DEA in measuring the priority of credit industry sections, there are limitations, which should be removed, and it can be considered by other researches. One of the limitations is that the A^2 -DEA adapt PWMs based on a primitive assessment. The other limitation is that both of models are limited to crisp evaluation, and fuzzy approaches can be explored in future investigations.

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